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ANALYSIS OF ENERGY POVERTY ACROSS SECTORS IN INDONESIA

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ABSTRACT

This study was conducted to analyze the influence of the household sector, transportation sector, other sectors, and energy prices on energy poverty in Indonesia. This study uses time series data from 1970-2022 using the ARDL model. The results showed that the household sector variable in the short term has a positive and significant influence on energy poverty, while in the long term, it also has a positive influence and is followed by a significant level. The transportation sector variable has a negative influence and is followed by a significant level of energy poverty in the short and long term. Other sector variables in the short and long term have no effect on energy poverty. The energy price variable in the short and long term also has no influence and is not significant on energy poverty in Indonesia.

Keywords: *Energy Poverty, Household sector, transportation sector, other sectors, energy price*

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INTRODUCTION

Indonesia is a country rich in energy resources, both unrenewable and renewable resources. However, the exploration of energy resources is more focused on unrenewable energy resources, while renewable energy is relatively underutilized. This condition causes the availability of unrenewable energy resources, especially crude oil, which is increasingly scarce (Elinur et al., 2010). Based on data from the International Energy Agency (2020), it is estimated that more than 80.1 million Indonesians do not have access to electricity, and millions rely on traditional biomass for cooking, resulting in health risks.

Energy poverty in Indonesia is a reality, but it often goes unnoticed and ignored. Thus, various policies and programs in the energy sector carried out by the central and local governments are not specifically aimed at addressing energy poverty. The basic energy needs of rural and urban communities require a diverse energy portfolio that represents the economic, social, and economic conditions of the country's natural resources region. This suggests that renewable energy such as hydro, solar, geothermal, wind and bio-energy have an important role to play in overcoming energy poverty in the country.

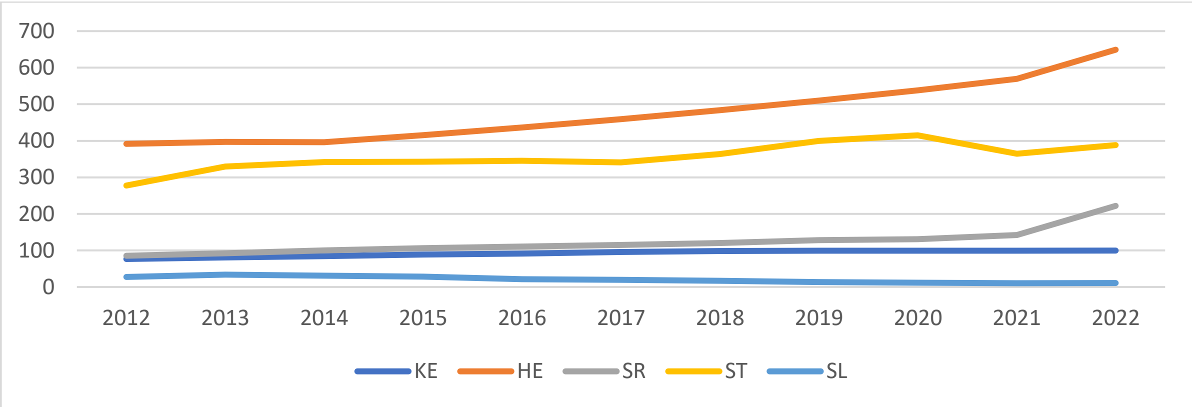
The energy sub-sector plays a significant role in sustainable development and the alleviation of energy poverty. In Indonesia, energy poverty can be seen from the level of electrification ratio and the availability and access to modern fuels for cooking. In 2020, the electrification rate in Indonesia only reached 64% while only 60% of villages in Indonesia were electrified (ESDM, 2020). Energy use in households is an important part of running a country's economy, especially to show the amount of final energy needed to meet the energy needs of the household sector which is part of the economic development process in Indonesia. Most household activities are supported by electrical energy, ranging from home lighting, electronic devices, and others.

Data from the Ministry of Energy and Mineral Resources (2022) also shows that by type, electricity dominates energy consumption in the household sector in 2022. The amount reached 70.28 million barrels of oil equivalent or equivalent to 47.17% of the total energy consumption in the household sector. Furthermore, Liquefied Petroleum Gas (LPG) consumption was recorded at 69.92 million barrels of oil equivalent. This is equivalent to 46.93% of total energy consumption in the household sector. Transportation is an important tool for modern society to facilitate the mobility of people and goods. Almost all energy used in the transportation sector uses fuel oil (BBM). Fuel oil used in the transportation sector is Premium, Pertalite, Pertamax, Solar, and Pertamina DEX (Martono, 2018).

The next factor that can affect energy poverty in Indonesia is the other sector. The other sector consists of three sub-sectors, namely agriculture, mining and construction. Energy demand in other sectors includes coal, diesel, biodiesel and electricity. Coal is used in the mining sub-sector, while diesel and biodiesel are used for generators as backup electricity supply (Oktaviani & Hartono, 2022). The sub-sectors that play a role in overcoming energy poverty are the household, transportation and other sectors. This is in accordance with the following figure:

Figure 1.

Development of energy poverty, energy prices and three sectors in indonesia



Source: Ministry of Energy and Mineral Resources, 2023

Based on the combined graph above, it explains that the lowest condition of energy consumption occurs in other sectors, while other sectors experience fluctuations but are not too significant. The peak condition or the highest condition of energy consumption in the five sectors is seen in the industrial and transportation sectors, the highest of which occurred in 2020. This is due to the rapid growth in the use of motorized vehicles which continues to increase and productivity in the industry which has also increased. This has caused the energy poverty rate in that year to also increase from the previous year.

Based on the figure above, it is known that the energy development of the Household sector in Indonesia has increased. The peak condition in the energy development of the Household sector in Indonesia occurred in 2022 amounting to 221.891 million SBM. This means that household activities in that year are highly dependent on the availability of energy supplies as fuel and electricity used to facilitate important needs in daily activities. This is in accordance with the statement of Mangari (2017) which states that the most important need in households is energy needs. Where, the household sector requires energy in meeting the needs of household activities such as cooking, lighting, heating or air conditioning, and others.

Energy poverty is challenging to measure and analyze because it is experienced personally within households or within the scope of a population. Hence, public policy governments address energy poverty and also study its causes, symptoms and impacts in society (Kotler & Amstrong, 2017). Hinz (2013) states that energy cannot be stored, energy requires a *reliable* supply and time adjustment with demand is needed. Meanwhile, Watson et al, (2012) state that electrical energy includes goods that cannot be touched or felt *intangible,* produced and purchased continuously. Energy has unique characteristics that differ from other physical products, namely that it has a natural monopoly, cannot be stored or has no inventory, must be produced continuously, and is not consumed as an end product.

Research conducted by Doukas & Marinakis (2020) states that energy poverty is widely understood as the inability of households to maintain an adequate level of energy services at an affordable cost. Then research conducted by Widodo (2018) which states that a significant determinant factor affecting energy poverty conditions is the household. Therefore, this study recommends development policies for Eastern Indonesia and the West Coast islands of North Sumatra prioritized on the availability of access to modern and adequate energy services. In addition to the national electricity problem that has become the government's current concern, addressing the problem of energy poverty in the dimension of traditional biomass fuel use also needs to be addressed immediately by targeting households that correspond to the determinants of energy poverty factors.

Based on previous studies that have been conducted, there are also those that discuss energy poverty, what distinguishes previous or previous research from the author's research is the analysis model used. Then on the object of research, namely not all previous studies used industrial and other sector variables. Because research on energy poverty is the latest research, there are very few previous studies that discuss research variables. Based on the description of the problems above, it is known that energy poverty causes conditions where people cannot enjoy modern energy services for both cooking and lighting purposes. Although Indonesia is a country with per capita energy consumption that exceeds the minimum consumption of modern energy, in reality, energy poverty still occurs in some parts of Indonesia.

LITERATURE REVIEW AND HYPHOTHESIS DEVELOPMENT

Energy Prices

Hinz (2013), states that energy cannot be stored, energy requires a reliable supply and time adjustment to demand is necessary. While Watson et al, (2012) stated that electrical energy includes goods that cannot be touched or seen (intangible), produced and purchased continuously. Energy has unique characteristics that are different from other physical products, namely that it has a natural monopoly, cannot be stored or has no supply, must be produced continuously, and is not consumed as an end product.

Energy Poverty

Energy poverty is a condition where humans cannot enjoy modern energy services either for cooking or lighting purposes. Although Indonesia is a country with per capita energy consumption exceeding the minimum consumption of modern energy should be, in reality, energy poverty still occurs in some parts of Indonesia. IESR conducted a literature study and analysis on energy poverty in Indonesia (Institute For Essential Service Reform, 2020).

Industrial Sector

Industry is an economic activity that processes raw materials, raw materials, semi-finished goods, and / or finished goods into goods with high value for their use, including industrial design and engineering activities (Lukman, 2017).

Household Sector

Energy is indispensable in carrying out Indonesia's economic activities, both for consumption needs and for production activities of various economic sectors. As a natural resource, energy must be utilized as much as possible for the prosperity of the community and its management must refer to the principle of sustainable development (Nasikun, 2018).

Commercial Sector

The commercial sector is an energy-consuming sector consisting of service providers and business equipment; Central Government, State Government, and local government; and other private and public organizations, such as religious, civic, or fraternal groups (Lukman, 2017).

Transportation Sector

The transportation sector is one of the links in the distribution network of goods and passengers that has developed very dynamically and plays a role in supporting political, economic, socio-cultural and security defense development (Widodo, 2018).

Other Sectors

This other sector consists of three subsectors, namely agriculture, mining and construction. A sector that has a very important role in the national economy is the agricultural sector. The agricultural sector has various businesses engaged in food crops, plantations, farming, fisheries, forestry and other services that are directly related to agriculture. The agricultural sector is also one of the sectors that requires energy to move in its field. The mining sector is a sector that plays a role in providing energy resources that will be needed in Indonesia's economic growth (Reksohadiprodjo, 2017). The mining sector includes industries in the field.

RESEARCH METHODS

This study aims to analyze energy prices, the household sector, the transportation sector and other sectors affect energy poverty, because overcoming energy poverty is one form of improving people's welfare. Therefore, it is the joint responsibility of the Energy and Mineral Resources (ESDM) sector to jointly alleviate energy poverty in the community. This was conveyed by Minister of Energy and Mineral Resources Darwin Zahedy Saleh. The Minister of Energy and Mineral Resources said, The Ministry of Energy and Mineral Resources needs support from all parties to encourage energy extension programs with the aim of improving people's welfare. The proportion of investment is not enough only from the Government, but it requires *non-government* companies and other stakeholders in the ESDM sector to encourage energy counseling programs and the Energy Award launched by the Government. This study uses quantitative data from 1970-2022 using the ARDL data model. The formulation is as below (Sugiyono, 2016).

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{n} \beta_1 \Delta Y_{t-1} + \sum_{i=0}^{n} \delta_1 \Delta Y_{t-1} + \varphi_1 Y_{t-1} + \varphi_2 X_{t-1} + \mu_t$$

Information:
β_0, β_1 : Short-run coefficients
δ_1, φ_2 : Long run ARDL coefficients
μ_t : Disturbance error (white noise)

The estimation method used is the Autoregressive Distributed Lag (ARDL) approach. The ARDL model was chosen because using ARDL will be able to see the effect of Y and X over time, as well as the effect of past Y variables on present Y. The steps of data analysis using the ARDL approach in research are as follows:

1. Testing the stationarity of the data.
   The data stationarity test is conducted to see if the data is integrated at the same order or not. If the data is integrated at the same order, the research can be done with cointegration methods such as the Engel-Granger method or the Johansen method or the Johansen and Juselius method. However, if the test results are integrated at different orders, the ARDL method will be used.
2. Selecting the ARDL model to be used as the basis for estimating the long-run and short-run coefficients. The ARDL model is selected based on the Schawarz Bayesian Criterion (SBC) which is able to select the smallest lag length or based on the Akaike Information Criterion (AIC) to select the maximum relevant lag length.
3. Testing the suitability of the selected ARDL model.
4. Perform ARDL bound test.

This test is conducted to determine the existence of long-term relationships (cointegration) and causality among the variables used in the model. ARDL bound test is conducted by estimating the ARDL general equation which in turn places each variable used in the model as a dependent variable. This test is conducted to determine the direction of causality of the variables in the model.

5. Estimating the long-run and short-run dynamics of the selected ARDL model.

RESULTS AND DISCUSSION

Unit root test is a data test to determine if the data used in a study is stationary or not. A set of data is declared stationary when the average value and variance of the time series data do not change systematically over time or are constant (Nachrowi and Haridus Usman, 2006). The tests often used in this unit root test are the Augmented Dickey-Fuller (ADF) test or the Phillips-Peron test. Both indicate the existence of a unit root as the null hypothesis. Unit root test results with Eviews 10 as in table 3. The test results are as follows:

Table 1.
ADF Unit Root Test Model

Variables	**Root Unit**	**Prob ADF**	**Description**
Energy Poverty (Y)	First Diff	0.0106	Stationary
Household Sector (X1)	First Diff	0.0049	Stationary
Transportation Sector (X2)	First Diff	0.0000	Stationary
Other Sectors (X3)	Level	0.0000	Stationary
Energy Price (X4)	First Diff	0.0000	Stationary

Source: Data Processed (2023)

From the table above in the ARDL method, the unit root test is not required to have stationary properties at the same difference level (as in the Engle-Granger and Johansen methods), but this is done to ensure that the variables used are stationary at the level or first difference. It is said to be stationary because the probability value is below (<0.05).

Unit root testing with the Augmented Dickey-Fuller (ADF) method provides stationarity output of the data summarized in the ADF test results show that Energy Poverty (PoV), Transportation Sector (Trans) as well as the Household sector (HH) and Energy Prices (PE) are stationary at first difference. While the Other sector (OS) is stationary at the level.

Autoregressive Distributed Lag Model

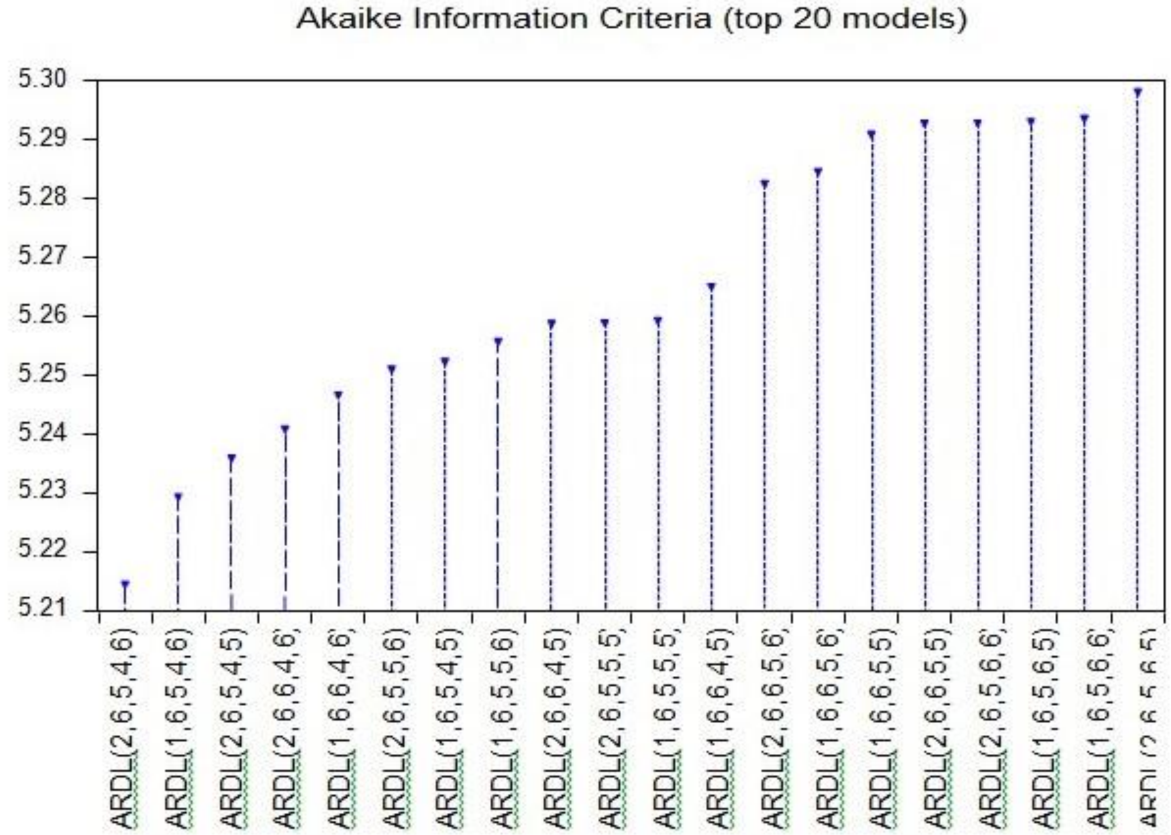
After conducting the stationarity test, the results show that there is one variable stationary at order I(0) (at level) and four variables are stationary at the same order I (1) (first difference level) and not at I (2), which is appropriate for the requirements of the Autoregressive Distributed Lag (ARDL) approach

Table 2.
ARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
POV(-1)	0.271013	0.183227	1.479109	0.1555
POV(-2)	-0.155453	0.146635	-1.060138	0.3024
LOGHH	4.135264	8.471421	0.488143	0.6310
LOGHH(-1)	-4.436712	22.94944	-0.193326	0.8488
LOGHH(-2)	31.40608	21.33987	1.471709	0.1575
LOGHH(-3)	41.15549	21.27464	1.934486	0.0681
LOGHH(-4)	26.17619	24.64986	1.061920	0.3016
LOGHH(-5)	-4.422925	25.54375	-0.173151	0.8644
LOGHH(-6)	-57.59428	21.51480	-2.676960	0.0149
LOGTRANS	-12.50399	9.165891	-1.364187	0.1885
LOGTRANS(-1)	28.00259	12.68670	2.207241	0.0398
LOGTRANS(-2)	-9.628964	12.05873	-0.798506	0.4344
LOGTRANS(-3)	21.53907	13.46850	1.599218	0.1263
LOGTRANS(-4)	1.720450	16.96556	0.101408	0.9203
LOGTRANS(-5)	-24.98319	12.39803	-2.015095	0.0583
LOGOS	-0.158478	0.552889	-0.286636	0.7775
LOGOS(-1)	0.415976	0.595697	0.698300	0.4934
LOGOS(-2)	-0.025147	0.600858	-0.041852	0.9671
LOGOS(-3)	0.121409	0.742323	0.163552	0.8718
LOGOS(-4)	2.306368	0.861846	2.676079	0.0149
LOGPE	-0.338721	4.578532	-0.073980	0.9418
LOGPE(-1)	-2.055417	6.194269	-0.331826	0.7437
LOGPE(-2)	1.336813	5.620115	0.237862	0.8145
LOGPE(-3)	1.715890	4.499437	0.381357	0.7072
LOGPE(-4)	-1.719209	3.398389	-0.505889	0.6188
LOGPE(-5)	-6.473542	3.309495	-1.956051	0.0653
LOGPE(-6)	-3.403069	3.036184	-1.120838	0.2763
C	87.28967	94.66860	0.922055	0.3681
R-squared	0.991622	Mean dependent var		70.07234
Adjusted R-squared	0.979717	S.D. dependent var		19.97389
S.E. of regression	2.844651	Akaike info criterion		5.214538
Sum squared resid	153.7487	Schwarz criterion		6.316754
Log likelihood	-94.54165	Hannan-Quinn criter.		5.629310
F-statistic	83.29286	Durbin-Watson stat		2.315999
Prob(F-statistic)	0.000000			

The results of model selection using the AIC value state that the ARDL (2,6,5,4,6) model is the best model with the smallest Akaike Criterion value of 5.21. This the general form of the ARDL (2,6,5,4,6) model.

Figure 2.
Akaike Information Criteria



Source: Data processed (2023)

Testing the suitability of the selected ARDL model needs to be done so that the research model formed does not violate econometric rules. Diagnostic testing of the ARDL (2,6,5,4,6) model will mainly be done by checking Autocorrelation and model stability. The Autocorrelation test on the ARDL (2,6,5,4,6) model will use the Breusch-Godfrey Lagrange Multiplier (BGLM) test, with the following results:

Table 3.
Autocorrelation Test Results

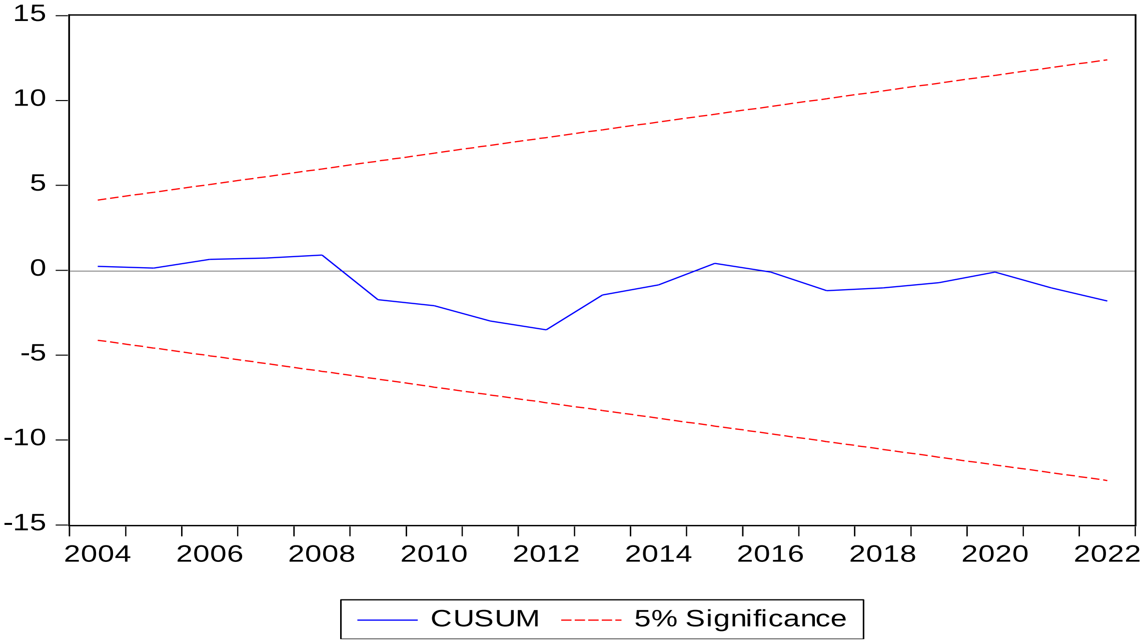
F-statistic	0.975115	Prob. F (2,15)	0.3998
Obs*R-squared	4.717307	Prob. Chi-Square (2)	0.0945

Source: Data processed (2023)

Based on the results of data processing as in table 5, it is known that Prob. Chi-Square for the BGLM test is 0.0945 which is greater than alpha 0.05. These results indicate that at the 95% confidence level the null hypothesis cannot be rejected, which means that there is no autocorrelation in the residuals of the ARDL model.

The ARDL model stability test in this study uses the CUSUM test with a 95% confidence level. The CUSUM test results for the ARDL (2,6,5,4,6) model in this study are as shown in Figure 1.
The stability of the model is determined from the position of the blue CUSUM line between the two red 5% significance lines. For this ARDL model, the CUSUM line is between the significance lines which proves that the ARDL (2,6,5,4,6) model is stable.

Figure 3.
Model stability test-Cusum test



The Bounds test is conducted to test the long-run association in the selected ARDL model. The results of this Bounds test will focus more on the F-statistic value. The F-statistic value will be compared with the Pesaran critical value at the 5% level. If the F-statistic has a value that exceeds the upper Bounds value, the null hypothesis stating that there is no long-run association is rejected, which means that the variables in the study move together in the long run.

Table 4.
Bound Test

Test Statistic	Value	Sign if.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	7.777794	10%	2.2	3.09
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size	47		Finite Sample: n=50	
		10%	2.372	3.32
		5%	2.823	3.872
		1%	3.845	5.15

Source: data processed (2023)

Based on the Bounds Test results for the ARDL (2,6,5,4,6) model in table 5, it can be seen that the F-statistic value of the model is 7.777794 which is greater than the upper bound value at the 5% level, and even greater than the upper bound at the 1% level. This proves that the five variables in this study namely Poverty, Household Sector, Transportation Sector, other sectors and Energy Prices are cointegrated in the long run or it can be said that the five variables move together in the long run.

Until the bound test is conducted, it is known that the five variables in this study have long-term cointegration. In the ARDL (2,6,5,4,6) model, the long run coefficients are obtained as in table 6. From the long run estimation results, it can be seen that the variables of Transportation, other sectors and energy prices have a negative and significant effect on poverty. The household sector variable has a positive and significant effect on poverty. This answers the phenomenon that occurred in the period 1970 - 2022 where the poverty rate continued to rise accompanied by a fairly high increase in energy prices, in this case fuel oil energy. This increase is quite influential on the increase in energy demand from the transportation sector of other sectors, and the most influential in the energy consumption sector for households. In other words, the effect of household energy consumption on poverty has a long-term relationship.

Table 5.
Short-Term Estimates and Long-Term Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(POV(-1))	0.155453	0.110067	1.412348	0.1740
D(LOGHH)	4.135264	6.913436	0.598149	0.5568
D(LOGHH(-1))	-36.72056	16.79301	-2.186658	0.0415
D(LOGHH(-2))	-5.314479	9.426621	-0.563774	0.5795
D(LOGHH(-3))	35.84101	13.93235	2.572502	0.0186
D(LOGHH(-4))	62.01720	13.15563	4.714117	0.0002
D(LOGHH(-5))	57.59428	18.07122	3.187073	0.0049
D(LOGTRANS)	-12.50399	6.492339	-1.925960	0.0692
D(LOGTRANS(-1))	11.35264	6.555879	1.731673	0.0995
D(LOGTRANS(-2))	1.723678	6.603591	0.261021	0.7969
D(LOGTRANS(-3))	23.26274	8.085793	2.876990	0.0097
D(LOGTRANS(-4))	24.98319	10.33621	2.417056	0.0259
D(LOGOS)	-0.158478	0.353163	-0.448738	0.6587
D(LOGOS(-1))	-2.402630	0.562932	-4.268060	0.0004
D(LOGOS(-2))	-2.427776	0.533627	-4.549577	0.0002
D(LOGOS(-3))	-2.306368	0.604909	-3.812750	0.0012
D(LOGPE)	-0.338721	3.459816	-0.097902	0.9230
D(LOGPE(-1))	8.543117	3.851653	2.218039	0.0389
D(LOGPE(-2))	9.879930	2.258148	4.375235	0.0003
D(LOGPE(-3))	11.59582	2.891719	4.010009	0.0007
D(LOGPE(-4))	9.876611	2.563455	3.852852	0.0011
D(LOGPE(-5))	3.403069	2.426463	1.402482	0.1769
CointEq(-1)*	-0.884440	0.115196	-7.677727	0.0000

Table 6.
Long run coefficient

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOGHH	41.17758	9.969148	4.130502	0.0006
LOGTRANS	4.687674	6.199830	0.756097	0.4589
LOGOS	3.007696	2.438549	1.233396	0.2325
LOGPE	-12.36630	5.977221	-2.068905	0.0524
C	98.69483	105.6237	0.934400	0.3618

Source: Data processed (2023)

Through the ARDL approach, we can also obtain short-term estimates that can be seen through the ECT or CointEq values. Through the cointegration test results in Table 6, it is known that the CointEq(- 1) value = -0.884440 and is significant at the 5% level, which means that there is short-term cointegration in this model. The CointEq coefficient will then be used to measure the speed of adjustment which is the speed of adjustment in response to changes. The ECT or CointEq value is valid if the coefficient is negative with a significant probability at the 5% level. In this study, the ARDL

(2,6,5,4,6) model has met these validity requirements, so in this study we can conclude that the model will go to equilibrium at a speed of 88.44% per month.

CONCLUSION

This study examines the analysis of energy poverty in Indonesia, and concludes that the household sector has a significant effect on energy poverty. The Transportation sector has no negative and insignificant effect on energy poverty. Other sectors have no and insignificant influence on energy poverty. And energy prices also have no influence and are insignificant on energy poverty in both the short and long term.

REFERENCES

Doukas, S & Marinakis, V. (2020). A building automation and control tool for remote and real time monitoring of energy consumption. Sustainable Cities and Society. vol. 6, pp. 11–15

Elinur., Ashefa & Trihono. (2018). Perkembangan Konsumsi dan Penyediaan Energi dalam Perekonomian Indonesia, Indones. J. Agric. Econ., vol. 2, no. 1, pp. 97–119

ESDM. (2022). Energi Sumber Daya Mineral. http://www. Esdm.go.id

Hinz, J. (2013). Modeling Day–Ahead Electricity Prices. Germany: Department Of Mathematics Dresden University of Technology.

International Energy Agency. (2020). Southeast Asia Energy Outlook. Paris: IEA

Kotler, P & Amstrong, G. (2017). *Prinsip-prinsip Pemasaran Edisi 13 Jilid 1.* Jakarta: Erlangga

Lukman. J. (2017). *Analisis Aplikasi Energi Terbarukan Pada Permintaan Dan Penyediaan Energi Listrik Serta Penurunan Emisi Di Jawa Timur.* Yogyakarta: Teknik Elektro UMY

Mangari, ES. (2017). Pengaruh Pendapatan Nasional Terhadap Pola Konsumsi Energi Sektoral Indonesia. Makassar: Universitas Hasanuddin.

Martono, R.M. (2018). *Manajemen Operasi Konsep dan Aplikasi*. Salemba Empat, Jakarta.

Nasikun. (2018). *Isu dan Kebijakan Penanggulangan Kemiskinan*. Universitas Gajah Mada.

Oktaviani & Hartono. (2022). Energy Poverty and Education: Empirical Evidence from Indonesia. Economics Development Analysis Journal. Vol (2)

Reksohadiprodjo, S. (2017). *Ekonomi Sumber Daya Alam dan Energi*. Yogyakarta: BPFE

Sugiyono. (2016). *Metodelogi Penelitian Kuantitatif, Kualitatif dan R & D*. Bandung: CV. Alfabeta.

Widodo, E. (2018). Kebijakan dan Strategi Pemasaran. Tanggerang Selatan: Universitas Terbuka.

Watson, A., Viney, H., & Schomaker, P. (2012). Consumer Attitudes to Utility Products: A Consumer Behaviour Perspective, Marketing Intelligence & Planning. Marketing Intelligence & Planning (Mip), Vol. 20 Iss 7 Pp. 394 - 404.